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Smart Farming for Sustainable Agriculture: A Systematic Review of Cost-Effectiveness, Barriers and Enablers

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ABSTRACT

Smart farming has been encouraged as a measure of improving the yield of agricultural produce with less harm to the environment. However, the factual information about its economic performance and implementation is mixed. The review brings together all the world research on the cost-efficiency of smart and climate-smart agriculture and pinpoints the drivers of its adoption and obstacles to it. Articles on English-language studies published in 2010-2025 were searched in various journals and using PRISMA principles, 112 empirical studies have been identified. Data were encoded based on technology type, geographic region, financial performance, sustainability impacts and adoption conditions. The vast majority of publications suggest that climate-sensitive activities, precision agriculture, IoT-based irrigation and digital decision-making, and smart energy system tend to raise profitability, create positive ratios of benefits to costs, and have brief payback. These interventions delivered reductions in water use, decreased input use, and increased resilience of the system as well. But, some capital intensive technologies, especially in marginal regions, were characterized by longer pay-back periods or negative net present values. The obstacles to adoption are high initial costs, limited access to credit, digital skills, insufficient infrastructure, increased risk perception and social inequity. The adoption was better where the farmers had access to subsidies or finance, targeted training, good connection, farmer-based advisory services, and where they were in peer groups. Policies and public investments must lower risk for smallholders and embed proven technologies in inclusive support systems. This is needed in order to ensure that smart farming can play its fair share in sustainable agriculture and rural livelihoods across the globe. These results demonstrate the significance of situational variables, structure, and facilitating processes during investment planning.

INTRODUCTION

Smart farming has emerged at the time when the pressure on agriculture is growing, and the need to deliver maximum results with limited resources becomes more crucial. Although food security is still maintained, the modern-day agriculture system has to simultaneously manage the growth of population, climate change, resource limitations, and the rising production prices, as well. Food and Agriculture Organization (FAO) estimates that the world population is expected to exceed 9.7 billion by 2050, meaning that food production will need about 60 percent without a corresponding increase in arable land (FAO, 2017). The traditional methods of achieving this demand are increasingly becoming impossible, thus pushing agriculture into data-driven technology-facilitated methods.

In this context, the term smart farming or digital agriculture refers to the implementation of technologies (Internet of Things (IoT), sensors, drones, big-data analytics and artificial intelligence, robotics, and cloud platforms) that allow monitoring and managing agricultural production more precisely (Wolfert *et al.,* 2017). Such technologies enable farmers to monitor the condition of soil moisture and crops, pest pressure, and the weather in real-time and make the necessary adjustments to inputs. The experience of precision agriculture and intelligent irrigation shows that these technologies can make progress in fertilizer and pesticide application by up to 30 percent, fuel consumption by approximately 10 percent, and yield reduction does not negatively affect yields (Balafoutis *et al.,* 2020). The large-scale irrigation control can actually save 20-50 percent of the water and preserve or even enhance crop productivity (Cáceres *et al.,* 2021). Thus, smart farming is a legitimate opportunity to increase productivity and decrease the strain on land, water, and ecosystems.

The economic aspects of smart farming are, however, much more complicated. Most smart agricultural systems involve huge initial costs in equipment, software, internet connectivity, and expertise. IoT packages and related infrastructure may cost USD 1,500 to USD 5,000 per hectare without the training and service maintenance expenses (World Bank, 2021). Existing large commercial farms in Europe, North America, and some of East Asia have been more addicted to the use of digital tools faster, facilitated by government subsidies, guidance, and well-established rural infrastructure (Papadopoulos *et al.*, 2024). Smallholders, in sharp contrast, which constitute over 570 million farms in various parts of the world, often have little access to capital, credit, digital literacy, and dependable connectivity, therefore, restricting their ability to invest and benefit in smart farming (Glaroudis *et al.,* 2020; Lowder *et al.,* 2016; World Bank, 2021).

At the same time, there is a growing amount of evidence that with proper conditions, smart farming may be

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financially appealing. Low-cost smart irrigation systems in Ukraine, sensor-based irrigation in Kherson Province, and decision-support tools in Southern Africa have positive Net Present Values (NPV), high Internal Rates of Return (IRR) and Benefit-Cost Ratios (BCR) significantly greater than one (Bazaluk *et al.,* 2022; Branca *et al.,* 2021; Sain *et al.,* 2017). The recent studies of the Australian IoT-enhanced hydroponics in Thailand and climate-smart agriculture in Nepal and Ghana also report strong returns and yield improvements as well as risk reduction (Duangpakdee *et al.,* 2024; Kpenekuu *et al.,* 2025; Poudel *et al.,* 2024). On the other hand, other studies have reported small or even negative returns in case of poor adoption of technologies, high cost of credit, weak markets, or uncontrolled climate risks (Komarek *et al.,* 2019; Mujeyi & Mudhara, 2020). This lack of homogeneity in results creates an uncertainty for farmers, advisers and policymakers.

Beyond the simple profit indicators, more questions can be asked about benefits allocation, under what circumstances they will be realized, and the overall implications to the society and the environment. The digital agriculture has been reviewed in reference to issues regarding data ownership, power, and how smart farming might contribute to the already existing inequalities, in case the access remains highly concentrated among big and capital-rich farms (Bacco *et al.,* 2019; Rose & Chilvers, 2018; Van der Burg *et al.,* 2021). According to the studies in social sciences, the adoption is not only determined by the economic returns but also by trust, perceived usefulness, ease of use, advisory networks, and policy incentives (Barnes *et al.,* 2018; Kuehne *et al.,* 2017; Yoon *et al.,* 2020). Parallel economic analyses use diverse indicators Return on Investment (ROI), Payback Period, NPV, IRR, and BCR, across time horizons and basic assumptions, which makes it difficult to compare across technologies and across regions (McCarthy *et al.,* 2017; Poudel *et al.,* 2024).

The available literature reviews have already enriched our knowledge of smart farming technologies, applications, and barriers to adoption, but they do not tend to combine a systematic synthesis of empirical data throughout the globe with an elaborate economic evaluation (Bacco *et al.,* 2019; De Alwis *et al.,* 2022; Mizik, 2021; Navarro *et al.,* 2020). Although numerous studies concentrate on the technical factors, environmental gains, or adoption patterns, the fiscal performance of technologies and their dynamics with sustainability and inclusion are only partial throughout the case studies. Besides, it features poor synthesis of the barriers and enabling conditions that form cost-efficacy in a variety of settings, especially in smallholders residing in low and middle-income countries (Glaroudis *et al.,* 2020; Javaid *et al.,* 2022; Su & Wang, 2021).

This study is aimed at filling this gap. It is based on the systematic review of 112 empirical studies and economic analyses, it summarizes international evidence on cost-efficiency of smart farming, especially standard financial indicators (ROI, NPV, IRR, BCR and payback measures), sustainability performance, and adoption process. In particular, the article (i) summarizes the financial performance outcomes of smart farming when compared with traditional practices in terms of regions and technologies, (ii) outlines the main barriers limiting the implementation of the technology to be cost-effective, and (iii) visualizes the enabling conditions to deliver both economic and sustainability benefits, which include policy support, financing models, advisory services, and institutional arrangements. In this way, it will attempt to present a better evidence base to farmers, policymakers, investors, and development partners who should decide when and where smart farming is a viable and fair investment.

MATERIALS AND METHODS

This study used a systematic literature review (SLR) design to synthesize global evidence on the cost-effectiveness, barriers, and enablers of smart farming. This was because the SLR approach is systematic and stepwise and transparent in identifications of extant research and screening and synthesizing it, a characteristic that was considered necessary in a topic that encompasses a wide range of technologies, geographic locations, and farm systems (Moher *et al.,* 2010). The study has utilized peer-reviewed journal articles, conference papers, technical reports, and credible institutional publications as the sole sources of secondary data, thus incorporating financial, environmental, and social orientations of smart farming in various settings.

The major academic databases such as Scopus, Web of Science and ScienceDirect were searched through literature searches which were reinforced using Google Scholar to pull out other relevant studies as well as gray literature carried out by credible organizations. Search queries used terms like smart farming, climate-smart agriculture, precision agriculture, ROI, NPV, IRR, BCR, net profit, and sustainability and used Boolean operators (AND/OR) to narrow the results. The first search gave over 210 records but upon de-duplication, about 193 distinct studies were obtained and scanned at the title and abstract stage according to a set of predefined inclusion and exclusion criteria. The studies were considered eligible when they focused on practices of smart farming or climate-smart agriculture.

The final selection was restricted to only empirical, modeling, or case-based studies that are published in English within the 2010-2025 period as they represent the time-frame when smart farming technologies were more developed and discussed. Sources based on purely theoretical work, duplicated records, and non-credible or non-peer-reviewed sources were eliminated. Only works that produced economic or sustainability results were included as well as studies that did not conduct technical performance solely. Screening of the full-text of the 193 studies resulted in a final sample of 112 peer reviewed technical papers which met all the criteria and therefore formed the core evidence base of this review. In PRISMA flow diagram (Figure 1), the total process of identification, screening, eligibility and inclusion is outlined in the manner recommended by the standard reporting recommendations of systematic reviews (Moher *et al.,* 2010).

The data were extracted systematically using a structured form on each of the 112 studies. The main areas were bibliographic information, geographical location, the type of smart agricultural technologies (e.g., IoT-based irrigation, drones, robotics, digital platforms, climate-smart agriculture), type of study (case study, field experiment, survey, or modeling), and financial indicators reported. Environmental and social consequences (saving of water, emissions, poverty or equity effect) were also noted as well as adoption factors (barriers, enablers, farmer perceptions and institutional support). The resulting information was then coded into thematic themes of financial performance, sustainability outcomes, and adoption conditions and allowed comparing the evidence across technologies, regions, and farm types and drawing general patterns and gaps in the evidence base.

The review also incorporated basic validity and reliability safeguards. The selection of the studies followed the PRISMA framework (Figure 1) that minimizes selection bias, and the selection of the sources was restricted to peer-reviewed or other credible institutional sources. The extraction form used was a standardized extraction form in all the 112 studies; this increased the level of consistency and replication of the analysis. Since the entire review was conducted using secondary data that was published; therefore, consideration of ethics focused on proper citation, fabrication avoidance, and intellectual property honoring.

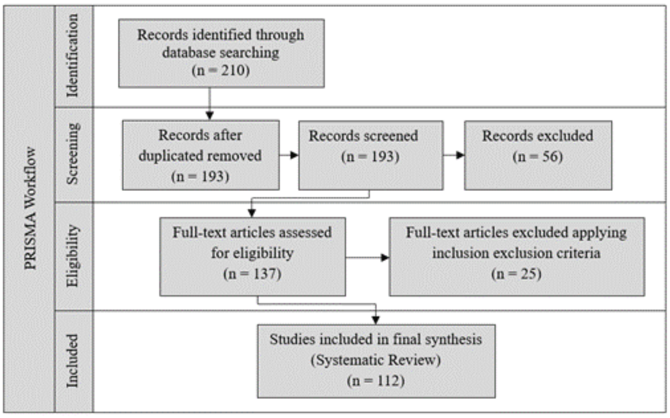

Figure 1: PRISMA Flow Diagram

RESULTS AND DISCUSSION

The systematic review summarized the findings of 112 empirical peer reviewed studies in the field of smart farming and other agri-technological interventions. Most of this evidence is Asian and European with smaller although significant parts found on Africa, North America, Oceania, and South America. As a result, the results represent a wide range of agricultural systems, including small-scale rice and maize production, large-scale horticulture, hydroponics, livestock production, and digitally facilitated value chains.

The sample had different major clusters of technology, such as climate-smart agriculture (CSA) practices (such as conservation tillage, improved crop varieties, and integrated soil-water-nutrient management); digital decision-support systems (DSS); Internet of Things (IoT) sensors and precision agriculture (PA); smart water and energy systems; and robotics or automated processes in production and post-harvest management. These technologies are found in very different mixes and are often part of more extensive bundles that in turn include training, extension or management and value-chain reorganization.

General Evidence on Cost-Efficiency

The results of the financial appraisal give strong evidence that the introduction of smart farming is cost-effective in most cases when the circumstances are favorable. An aggregation of the 112 studies based on geographic region showed that 29 cases reported a positive benefit-cost ratio (BCR>1), 21 reported high internal rates of return (IRR), 16 reported positive returns on investment (ROI), 11 reported positive net present value (NPV), 15 reported comparatively short payback periods, and 25 reported positive net profits relative to conventional practices. These figures are a sub-set of the corpus where full financial indicators were reported, and which were comparative to each other.

At regional level, Africa and Asia show particularly strong financial signals. BCR reported BCR>1 in seven studies, positive IRR in six studies, positive ROI in four studies, positive NPV in one study, short payback periods in five studies and positive net-profit in six studies. In Asia, ten studies have reported BCR which is greater than 1, six high IRR values, five positive ROI values, seven positive NPVs, four short payback period and six positive net profits. The same positive evidence was also observed in Europe and North America, and less financial metrics were reported in Oceania and South America, which can be partly explained by smaller sample sizes.

Technology-Specific Financial Performance

When the data is re-aggregated on a basis of technology cluster as opposed to geographic region, a better trend of financial results is realized. Table 1 presents the frequency of the association between each category of smart-farming and the unequivocally positive financial results in the studies reviewed in its review.

All in all, these data show that the most common

Table 1: Frequency of positive financial outcomes by technology

Technology cluster	BCR >1	IRR (high)	ROI (+)	NPV (+)	Payback (short)	Net profit (+)
Climate-smart agriculture (CSA)	15	12	8	4	9	13
Decision support systems (DSS)	9	7	5	4	7	9
Internet of Things (IoT)	7	5	4	3	4	7
Precision agriculture (PA)	13	9	5	4	7	11
Energy / renewables	10	6	5	3	4	8
Robotics & automation	4	3	2	2	3	4
Value-chain & digital platforms	11	9	5	5	5	10
Total	89	65	40	29	42	70

indicators are positive BCR and net-profit results, then there are good IRR and reduced payback. The highest number of positive BCR results are produced in CSA and PA, whereas DSS and value-chain platforms are always profitable when they allow making the best decisions or getting better access to the market. IoT based solutions, robotics, and renewable-energy solutions also provide positive payoffs, but generally in more capital intensive settings (i.e., smart green houses, automated irrigation, or energy efficient storage).

The case studies in the study background demonstrate an example of the realization of these quantitative indicators on the ground. To give one example, low-cost smart irrigation in Ukraine and climate-smart irrigation packages in India both are associated with favorable BCRs and IRRs in addition to increased yields and water-use efficiency (Bazaluk *et al.,* 2022; Kakraliya *et al.,* 2022). In the United States, smart decision-support tools have the potential to increase a bottom line by a value of profit per hectare, which is achieved through optimization of fertilizer and inputs use, compared to CSA portfolios in Ghana and Nepal showing that diversified practices can be profitable even to smallholders when labor and risk are managed well (Mujeyi & Mudhara, 2020; Pope & Sonka, 2020; Poudel *et al.,* 2024).

Sustainability Outcomes Linked to Cost-Effectiveness

The study also examined how cost-effective smart farming interventions contribute to the three pillars of sustainability. Table 2 summaries selected examples that explicitly report both financial gains and sustainability co-benefits.

Investigations of existing literature always indicate that

Table 2: Cost-effective smart farming and sustainability outcomes

Technology / Intervention	Economic outcomes	Environmental outcomes	Social outcomes	Key References
CSA packages (conservation tillage, improved varieties, integrated soil–water–nutrient management)	Higher yields, increased net income, positive BCR and IRR	Improved soil organic matter, reduced erosion, better water retention	More stable production, improved food security, reduced vulnerability	Akinyi *et al.,* 2022; Branca *et al.,* 2021; Komarek *et al.,* 2019; Kpenekuu *et al.,* 2025; Mizik, 2021; Mujeyi & Mudhara, 2020; Poudel *et al.,* 2024; Sain *et al.,* 2017.
DSS and digital advisory services	Higher profits per hectare, improved input-use efficiency	Reduced fertilizer and chemical overuse, less pollution	Better decision-making, reduced information gaps	Eastwood *et al.,* 2019; Giusti & Marsili-Libelli, 2015; Mohamed *et al.,* 2021; Navarro-Hellín *et al.,* 2016; Papadopoulos *et al.,* 2024.
IoT-enabled smart irrigation and hydroponics	Higher returns per unit of land or water, shorter payback	Significant water savings, more efficient energy use	More predictable production, potential for off-season employment	Al-Ali *et al.,* 2019; Bazaluk *et al.,* 2022; Cáceres *et al.,* 2021; Duangpakdee *et al.,* 2024; Elijah *et al.,* 2018; Komarek *et al.,* 2019; Papadopoulos *et al.,* 2024; Poudel *et al.,* 2024.

Precision agriculture (PA) technologies	Increased profitability through input savings and yield gains	Reduced over-application of fertilizers and pesticides	Skill upgrading for operators, potential for new service jobs	Balafoutis *et al.,* 2020; Barnes *et al.,* 2018; Nowak, 2021; Papadopoulos *et al.,* 2024; Pope & Sonka, 2020; Rose & Chilvers, 2018.
Smart energy (solar pumps, renewables in greenhouses)	Lower operating costs over time, reduced fuel expenditure	Reduced greenhouse gas emissions, cleaner energy use	Improved reliability of services (e.g., irrigation), fewer fuel shocks	Al-Ali *et al.,* 2019; Bazaluk *et al.,* 2022; Elijah *et al.,* 2018; Kakraliya *et al.,* 2022; Komarek *et al.,* 2019; Papadopoulos *et al.,* 2024.

the benefits related to the economy and the environment are concomitant, and the farm that manages smart irrigation, climate smart agriculture (CSA) programs, or even precision input management tend to be more profitable in comparison with the outcome of the reduction of water usage, chemical intensity, or energy expenditure. However, some of them have indicated that the initial capital investment is high and that the payoff could not be achieved until several consecutive growing seasons, which also shows the importance of the payback period calculation and consideration of risk factors during the decisions of farmers (Basso & Antle, 2020; Komarek *et al.,* 2019).

Smart farming has a less homogeneous effect on social aspects. There are technologies that prove to be beneficial in terms of labor conditions and less manual labor, including automated harvesting machinery or smart greenhouse companies. On the other hand, additional innovations can increase the need to have technical skills or delegate the decision-making process to outside service providers or online platforms. The salience of social benefits is enhanced when smart farming is incorporated in supportive advisory networks and in conditions where farmers are not covered by such support systems, digital exclusion and equity differences are likely to increase further (Akinyi *et al.,* 2022; Su & Wang, 2021).

Comparative Performance: Smart vs. Conventional Practices

Agriculture is shifting away to systems based on digital technologies, as opposed to labor-intensive, experience-based approaches to agricultural production. Traditional agriculture is prone to use homogenous application rates of fertilizers, pesticides and water which often face over-use, wastefulness and soil erosion, and are increasingly challenged by rising costs, climatic pressures and sustainability demand (FAO, 2017). Smart farming, in contrast leverages the internet of things, artificial intelligence, unmanned aerial vehicles, robotics, and data analytics to provide real-time management decisions (Table 3) that are site-specific (Wolfert *et al.,* 2017). Evidence shows that precision irrigation can save 25–50% of water in countries such as China, Kenya, India and the Philippines (Bazaluk *et al.,* 2022; Papadopoulos *et al.,* 2024), while fertilizer and pesticide use can be cut by 30–50% without reducing yields (Balafoutis *et al.,* 2020).

Socially, smart farming has the potential to deliver economic returns in large quantities when adjusted to local environments. As an example, the hydroponic systems in Thailand achieved above 130 percent in one year (Duangpakdee *et al.,* 2024); climate smart agriculture programs in Ghana reported higher benefit-cost ratios of 1.9: 1 and extra over USD 1,000 in net gains (Kpenekuu *et al.,* 2025); and the implementation of digital tools in the United States added a benefit-cost ratio of 9.7: 1 and added USD 90 per acre in net earnings (Pope & Sonka, 2020). On the other hand, some of the interventions, like solar-powered maize water management in Nepal, are not economically viable, with long payback periods and negative net present values (Poudel *et al.,* 2024). Smart farming can decrease the workload of manual labor and decrease chemical pollution, whereas it can eliminate unskilled labor without specific reskilling courses (Papadopoulos *et al.,* 2024; Rose & Chilvers, 2018). Therefore, although smart farming tends to increase efficiency, profitability, and sustainability compared to traditional farming, high-startup costs, lack of digital skills, and insufficient infrastructure remain major obstacles to the mass adoption, especially in less developed countries.

Table 3: Comparison between Smart Farming and Conventional Farming

Aspect	Conventional Farming	Smart Farming	References
Input Use	Uniform application of fertilizers, pesticides, and water, often leading to overuse	Site-specific, optimized through IoT sensors, drones, and VRT	Balafoutis *et al.* (2020); Papadopoulos *et al.* (2024)
Water Management	Inefficient irrigation with high wastage	Precision irrigation reduces water use by 25–50%	Bazaluk *et al.* (2022); Papadopoulos *et al.* (2024)
Productivity	Yields improve mainly through higher input use	Yields rise by 20–25% with lower inputs	Papadopoulos *et al.* (2024)

Economic Returns	Lower returns, vulnerable to shocks	High ROI, strong BCR (e.g., 9.7:1 in U.S.), faster payback	Duangpakdee *et al.* (2024); Kpenekuu *et al.* (2025); Pope & Sonka (2020)
Labor	Labor intensive, with exposure to chemicals	Automation reduces labor needs, improves safety	Rose & Chilvers (2018); Papadopoulos *et al.* (2024)
Environmental Impact	High fertilizer and pesticide use causing soil and water degradation	Reduced emissions, fertilizer savings of 30%, pesticide cuts of up to 50%	Balafoutis *et al.* (2020); Papadopoulos *et al.* (2024)
Adoption Barriers	Low upfront costs, but inefficiencies persist	High initial cost, requires digital literacy and infrastructure	Ahmed *et al.* (2024); Poudel *et al.* (2024)

Barriers to Smart Farming Adoption

The move toward smart farming is up against many challenges (Table 4) that help explain why adoption remains slow, especially among smallholder farmers in developing countries, even when technologies are shown to be profitable and sustainable.

The biggest visible obstacle is the high initial capital requirement. Internet of Things (IoT), sensors, unmanned aerial vehicles, automated irrigation systems, and renewable energy use require significant amounts of money, which is usually inaccessible to most of the smallholders. In Ghana, there were also signs of long-term profitability, but farmers did not show interest in climate-smart agriculture (CSA) practices because of the lack of initial investment funds (Akinyi *et al.,* 2022). On the same note, CSA in Nepal generated positive net present values and internal rates of return; however, the initial cost was discouraging to economically poor farmers (Poudel *et al.,* 2024). An example of such a trend is the case of hydroponics in China: IoT-based hydroponic celery grew resulted in a 131% profit and a payback period of less than two years, but smallholders were still unable to afford the initial investment and advanced infrastructure (Duangpakdee *et al.,* 2024). Therefore, profitability is not sufficient, the affordability of technologies is a pre-condition to their adoption.

A second obstacle is moderate digital illiteracy and technical capacity of farmers. Smart farming implies the analysis of sensor data, using mobile platforms, and maintenance of multifaceted systems. Numerous smallholders, especially in rural settings, have little to no formal education experience and have little exposure to digital technologies. Su and Wang (2021) highlighted that the low level of digital literacy is one of the most powerful adoption obstacles; farmers are not likely to utilize the technologies they do not understand. In South Korea, farmers of older age were less likely to accept the smart farming because of the views on digital solutions as something intimidating and the willingness to continue using traditional approaches (Yoon *et al.,* 2020). Poor extension services and lack of communication in Ghana hindered the benefits of CSA into understandable terms and this limited its adoption despite its proven profitability (Kpenekuu *et al.,* 2025).

The lack of infrastructures also brings extra limitations of adoption. The success of smart farming is dependent on the availability of electricity, irrigation systems, internet services, and cell phone services. In Ethiopia, CSA was inadequately enabled by insufficient infrastructure, as farmers were not connected, reliable in irrigation, and power, hence even low-cost smart practices could not be fully realized (Komarek *et al.,* 2019). The CSA choices based on guaranteed irrigation or storage were not easily adopted in Nepal due to the lack of the necessary facilities in most rural areas (Poudel *et al.,* 2024).

Risk perception and trust also become main factors. Agriculture is inherently uncertain and in most cases, the smallholders tend to be risk-averse. Even in Ghana, farmers did not adopt CSA practices that were not immediately beneficial; those with long payback periods were unattractive to adopt even when they showed future profitability (Kpenekuu *et al.,* 2025). On the same note, increased adoption in Nepal was experienced when farmers had direct participation in cost-benefit analysis, which created confidence in the results (Poudel *et al.,* 2024). Past failures may foster suspicions that will make farmers doubt the new programs regardless of the potential benefits.

These challenges are worsening due to social inequality and cultural dimensions. Credit, land, training and networks access is not even. Financial and informational resources available to richer farmers in Ghana were more predisposed to CSA adoption, but poorer farmers, women, and the youth were subjected to systematic disadvantages (Kpenekuu *et al.,* 2025). Male headed households in Nepal registered higher propensity to adopt CSA as compared to female headed households (Poudel *et al.,* 2024). Such dynamics highlight an actual threat that smart farming can deepen the divide between rich and poor farmers. Attachment to the traditional practices also hinders adoption. The adoption of smart farming was limited by the preference of older farmers in Korea to the traditional approach (Yoon *et al.,* 2020). In some of Africa and South Asia, digital tools were sometimes viewed as not necessary or reliable as compared to long established practices.

Adoption of smart farming is faced with some serious barriers that can explain the slow pace of adoption across the world. Profitability isn't sufficient, though, farmers must also be able to afford, understand, and

Table 4: Barriers to Smart Farming Adoption

Barrier	**Description**	**Impact**	**Example**	**References**
High Costs	High upfront costs of equipment	Prevents smallholder adoption	IoT hydroponics in China too costly for smallholders	Duangpakdee *et al.,* 2024
Skills Gaps	Lack of technical capacity	Farmers cannot use digital tools	Digital literacy barriers in China and Korea	Su & Wang, 2021; Yoon *et al.,* 2020
Infrastructure	Poor connectivity and electricity	Limits digital platforms	Infrastructure gaps in Ethiopia and Nepal	Komarek *et al.,* 2019; Poudel *et al.,* 2024
Risk Perception	Farmers avoid uncertain returns	Low adoption of long-payback practices	Ghana CSA with unclear benefits avoided	Kpenekuu *et al.,* 2025
Inequality	Unequal access for women & poor	Benefits concentrated among wealthy	CSA adoption higher among wealthier men	Akinyi *et al.,* 2022
Cultural Resistance	Preference for traditional methods	Slow adoption	Older farmers in Korea resist new tools	Yoon *et al.,* 2020

trust technologies. Without addressing aspects of high costs, knowledge gaps, infrastructure limitations, risk perceptions, and inequality, smart farming runs the risk of being accessible only to large-scale or wealthier farmers. In order for these barriers to be overcome, to achieve broad and equitable adoption, they must be systematically addressed by policymakers, institutions and technology designers.

Enablers of Smart Farming Adoption

Smart farming is facing multiple challenges; however, deliberate use of strong enablers can speed up the process. The enablers (Table 5) include conditions, policy mechanisms, and innovations that make risk and cost reduction, development of skills and confidence, and development of trust and use of emerging technologies by farmers. When all these conditions are met, the probability of adoption will become higher and allow the advantages of smart farming to spread over a more extensive range of agricultural participants and environments.

One of the most effective enablers is policy support. Governments can also modify the economic calculus and perceived risk of smart farming through provisions of subsidies, training and conducive institutionalized environments. In South Korea, adoption of smart farming has increased significantly due to introduction of subsidies and demonstration programs, since farmers felt that they were sharing financial risk (Yoon *et al.*, 2020). In Ethiopia, the transition of climate-smart agriculture (CSA) as a niche concept to wider scales was supported by the presence of national strategies that clearly integrated the concept of climate-smart practices into a plan of agricultural development along with an extension service (Komarek *et al.,* 2019). Agreement to CSA by smallholder farmers in Nepal was more prone to reduction in initial expenditure by grants or group-based finance, which highlights the potential of fiscal policies to open the door to resource-poor actors (Poudel *et al.,* 2024).

Another enabler that is critical is capacity building. Smart farming devices can only be helpful provided that farmers have the necessary knowledge and trust to use them. In Ghana, the probability of CSA adoption was heightened due to training programs which in part created space of peer learning as the early adopters could help neighboring farmers to implement new skills that were learned through the training programs (Kpenekuu *et al.,* 2025). Su and Wang (2021) also noted that the training had to be referenced to the realities of the farmers: easy-to-use resources, intuitive dashboards, local-language mobile apps, and teaching and learning methods should be participatory to address poor digital literacy and concerns regarding complexity.

Simple digital and physical infrastructure is also a requirement. Smart farming requires the internet, proper electricity, and low-cost devices. In Ethiopia, a lack of electricity and connection was a major hindrance to the digital platform and CSA scaling (Komarek *et al.,* 2019). The same trends were observed in Nepal, where the CSA initiatives based on irrigation or weather-observing services were more sustainable in communities that had previously enjoyed the benefits of infrastructure projects (Poudel *et al.,* 2024). This means that the government need not rely on rural electrification and broadband only as an element of the developmental agenda; it is a requirement of digital agriculture.

Financial innovation helps the farmer in dealing with large initial expenditure. Risk sharing and cost reduction is possible through microfinance, cooperatives, digital credit and group based investments. The chances of using CSA were found to be significant in Ghana when the farmers had access to credit programs; otherwise, even the profitable practice had not been available (Kpenekuu *et al.,* 2025). In Nepal, the exposure was in fact diversified in cooperatives that collectively acquired irrigation equipment (Poudel *et al.,* 2024). The adoption can also be helped with insurance products in order to protect farmers against climate and yield risks in case of experimentation.

Hand on illustrations and involvement techniques are effective trust constructors. The innovations will be more acceptable to farmers when they can see and attest results. The adoption increased in Nepal with the farmers actively participating in participatory cost-benefit analyses; participation in the computations raised confidence in the outcomes (Poudel et al., 2024). The practice of demonstration farms in Ghana, where CSA was demonstrated, lowered the uncertainty level and made the benefits perceived as real (Kpenekuu *et al.,* 2025). Su and Wang (2021) further claim that farmer-centered design where tools are localized to local needs and practices quickens and stabilizes the adoption.

Last but not least, the enabling role is played by social networks and collective action. Knowledge sharing, sharing of equipment at reduced costs and better terms with suppliers are availed through community organization, cooperatives and farmer groups. In Ghana, these networks allowed adoption by allowing farmers to share equipment, exchange information and share solutions to problems (Kpenekuu *et al.*, 2025). Such networks contribute to assuring successful adoption beyond the individual decision-making process but as a shared process, which is especially relevant to smallholders.

Table 5: Enablers of Smart Farming Adoption

Enabler	**Description**	**Example**	**References**
Policy Support	Subsidies, strategies, institutional backing	National CSA scaling in Ethiopia	Komarek *et al.,* 2019
Capacity Building	Training & farmer education	CSA adoption improved with training in Ghana	Kpenekuu *et al.,* 2025
Infrastructure	Electricity & internet for IoT systems	Infrastructure gaps limited CSA in Ethiopia	Komarek *et al.,* 2019
Financial Innovations	Credit, microfinance, insurance	Credit access improved adoption in Ghana	Kpenekuu *et al.,* 2025
Demonstration	Farmer involvement & proof of benefits	Participation boosted CSA adoption in Nepal	Poudel *et al.,* 2024
Social Networks	Collective action & knowledge sharing	Cooperatives facilitated adoption in Ghana	Kpenekuu *et al.,* 2025

In general, adoption is determined by the balance between barriers and enablers. Expenses, skills, low infrastructure, and risk perception are some of the factors that hinder development, and subsidies, education, investing in infrastructure, financial instruments, and participatory and community-based development are some of the factors that drive development. In order to achieve all the broad economic, environmental, and social benefits of smart farming, enabling conditions should be actively enhanced, and the accessibility of technologies and their appeal to smallholders should be emphasized as a priority, not among richer farmers.

Discussion

In this study, it is demonstrated that smart farming as an investment is more likely to be productive and sustainable, although these advantages are not evenly distributed and highly context-dependent. In the whole sample of 112 studies, most smart farming interventions were reported as positive NPV, IRR, BCR, ROI and net profit, particularly of climate-smart agriculture (CSA), IoT-based irrigation and hydroponic systems. CSA packages in sub-Saharan Africa, India and Nepal, and IoT irrigation or hydroponics in China, repeatedly produced short payback and high returns, which prove that smart farming can be ready to outperform conventional ones when technologies are suitably adjusted to local conditions (Akinyi *et al.,* 2022; Duangpakdee *et al.,* 2024; Kakraliya *et al.,* 2022; Kpenekuu *et al.,* 2025; Poudel *et al.,* 2024).

Meanwhile, the results warn against considering smart farming as a sure commercial gain. Robotics and high-tech greenhouses as options associated with capital-intensive features aroused ambivalent outcomes due to high fixed costs and dependence on the subsidies that had a weak impact on profitability (Yoon *et al.,* 2020). Examples of interventions with a long payback period or negative NPV include solar irrigation of maize in marginal locations, which shows that the choice of technology is just as significant as the underlying innovation (Kakraliya *et al.,* 2022; Poudel *et al.,* 2024). The review then advocates the application of a comprehensive financial toolbox (NPV, IRR, BCR, ROI, payback and net profit) as opposed to headline yield gains alone.

One of the contributions that the synthesis made is to demonstrate that cost-effectiveness and sustainability tend to support one another. The majority of the most lucrative ones also decreased the use of water, fertilizer and energy and positively impacted margins and the environment (Akinyi *et al.,* 2022; Kakraliya *et al.,* 2022). CSA in Ethiopia increased GDP and reduced emissions and poverty and smart irrigation in Ghana reduced water use by approximately a half and increased returns (Komarek *et al.,* 2019; Kpenekuu *et al.,* 2025). Nonetheless, the review has identified trade-offs, in that, energy-intensive controlled-environment systems may achieve high ROI, but increasing concerns associated with equity and carbon footprints unless accompanied with low-carbon power that is affordable (Duangpakdee *et al.,* 2024; Kakraliya *et al.,* 2022).

Lastly, it is evident that profitability is not a sufficient measure of adoption. The costly nature of the initial investments, a weak infrastructure, and limited digital capabilities and social disparities discourage adoption, particularly among the smallholders, women, and older farmers (Komarek *et al.,* 2019; Poudel *et al.,* 2024; Su & Wang, 2021; World Bank, 2021; Yoon *et al.,* 2020). When the cost benefit outcomes are seen, risk is lowered by subsidies and credit, and participation and training are incorporated into the programs, adoption can be improved (Akinyi *et al.,* 2022; Kpenekuu *et al.,* 2025; Poudel *et al.,* 2024). All in all, smart farming is not a silver bullet, but a collection of context-sensitive options that needs to be successful due to good economics, supportive policies and inclusive design.

CONCLUSION

This review shows that smart farming can be both cost-effective and sustainability-enhancing, but only under the right conditions. Across 112 studies, many climate-smart agriculture (CSA) practices, precision technologies, IoT-based irrigation and digital tools delivered positive NPV, IRR, BCR and net profits, often alongside reduced water use, lower input intensity and greater climate resilience (Akinyi *et al.,* 2022; Duangpakdee *et al.,* 2024; Kakraliya *et al.,* 2022; Papadopoulos *et al.,* 2024). On the other hand, some interventions, e.g. capital-intensive or inefficiently-selective technologies, had payback times that were longer or had negative NPV, highlighting that contextual conditions, choice of crop, and market peculiarities had as great an influence as the technology itself (Komarek *et al.,* 2019; Poudel *et al.,* 2024).

The review also explains that profitability is not an adequate motivation toward adoption. High initial cost, poor infrastructure, low digital literacy, and systemic inequalities have continued to shut out a large number of smallholders, women and older farmers to smart farming opportunities (Kpenekuu *et al.,* 2025; Su & Wang, 2021; World Bank, 2021; Yoon *et al.,* 2020). Rates of adoption are enhanced in cases where the risk is risk-reduced with the help of subsidies and credit facilities, where training and participatory appraisal processes assist in establishing a feeling of confidence and where digital infrastructure and governance are specifically tailored to enhance inclusiveness (Akinyi *et al.,* 2022; Kpenekuu *et al.,* 2025; Poudel *et al.,* 2024).

In general, smart farming cannot be thought of as one single solution, but as a collection of options that are related to each other. In order to realize its potential as a sustainable agricultural country, policy and investment should focus on enabling proven technologies to be accessible, understandable and credible to smallholders; further investigation should focus on increasing evidence generation on the long-term, distributional and systemic effects.

REFERENCES

Ahmed, B., Shabbir, H., Naqvi, S. R., & Peng, L. (2024). Smart agriculture: Current state, opportunities, and challenges. *IEEE Access, 12*, 144456–144478. https://doi.org/10.1109/ACCESS.2024.3471647

Akinyi, D. P., Ng'ang'a, S. K., Ngigi, M., Mathenge, M., & Girvetz, E. (2022). Cost-benefit analysis of prioritized climate-smart agricultural practices among smallholder farmers: Evidence from selected value chains across sub-Saharan Africa. *Heliyon, 8*(4), e09228. https://doi.org/10.1016/j.heliyon.2022.e09228

Al-Ali, A., Nabulsi, A. A., Mukhopadhyay, S., Awal, M. S., Fernandes, S., & Ailabouni, K. (2019). IoT-solar energy powered smart farm irrigation system. *Journal of Electronic Science and Technology, 17*(4), 100017. https://doi.org/10.1016/j.jnlest.2020.100017

Bacco, M., Barsocchi, P., Ferro, E., Gotta, A., & Ruggeri, M. (2019). The digitisation of agriculture: A survey of research activities on smart farming. *Array, 3–4*, 100009. https://doi.org/10.1016/j.array.2019.100009

Balafoutis, A. T., Van Evert, F. K., & Fountas, S. (2020). Smart farming technology trends: Economic and environmental effects, labour impact, and adoption readiness. *Agronomy, 10*(5), 743. https://doi.org/10.3390/agronomy10050743

Barnes, A., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., Van der Wal, T., & Gómez-Barbero, M. (2018). Exploring the adoption of precision agricultural technologies: A cross-regional study of EU farmers. *Land Use Policy, 80*, 163–174. https://doi.org/10.1016/j.landusepol.2018.10.004

Basso, B., & Antle, J. (2020). Digital agriculture to design sustainable agricultural systems. *Nature Sustainability, 3*(4), 254–256. https://doi.org/10.1038/s41893-020-0510-0

Bazaluk, O., Havrysh, V., Nitsenko, V., Mazur, Y., & Lavrenko, S. (2022). Low-cost smart farm irrigation systems in Kherson Province: Feasibility study. *Agronomy, 12*(5), 1013. https://doi.org/10.3390/agronomy12051013

Branca, G., Arslan, A., Paolantonio, A., Grewer, U., Cattaneo, A., Cavatassi, R., Lipper, L., Hillier, J., & Vetter, S. (2021). Assessing the economic and mitigation benefits of climate-smart agriculture and its implications for political economy: A case study in Southern Africa. *Journal of Cleaner Production, 285*, 125161. https://doi.org/10.1016/j.jclepro.2020.125161

Cáceres, G., Millán, P., Pereira, M., & Lozano, D. (2021). Smart farm irrigation: Model predictive control for economic optimal irrigation in agriculture. *Agronomy, 11*(9), 1810. https://doi.org/10.3390/agronomy11091810

De Alwis, S., Hou, Z., Zhang, Y., Na, M. H., Ofoghi, B., & Sajjanhar, A. (2022). A survey on smart farming data, applications and techniques. *Computers in Industry, 138*, 103624. https://doi.org/10.1016/j.compind.2022.103624

Duangpakdee, K., Thananta, G., & Sukpancharoen,

S. (2024). IoT enhanced deep water culture hydroponic system for optimising Chinese celery yield and economic evaluation. *Smart Agricultural Technology, 9*, 100545. https://doi.org/10.1016/j.atech.2024.100545

Eastwood, C., Klerkx, L., Ayre, M., & Dela Rue, B. (2019). Managing socio-ethical challenges in the development of smart farming: From a fragmented to a comprehensive approach for responsible research and innovation. *Journal of Agricultural and Environmental Ethics, 32*(5–6), 741–768. https://doi.org/10.1007/s10806-017-9704-5

Elijah, O., Rahman, T. A., Orikumhi, I., Leow, C. Y., & Hindia, M. N. (2018). An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges. *IEEE Internet of Things Journal, 5*(5), 3758–3773. https://doi.org/10.1109/JIOT.2018.2844296

Food and Agriculture Organization of the United Nations. (2017). *The future of food and agriculture: Trends and challenges*. FAO.

Giusti, E., & Marsili-Libelli, S. (2015). A fuzzy decision support system for irrigation and water conservation in agriculture. *Environmental Modelling & Software, 63*, 73–86. https://doi.org/10.1016/j.envsoft.2014.09.020

Glaroudis, D., Iakovidis, D. K., & Chatzimisios, P. (2020). Survey, comparison and research challenges of IoT application protocols for smart farming. *Computer Networks, 168*, 107037. https://doi.org/10.1016/j.comnet.2019.107037

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Enhancing smart farming through the applications of Agriculture 4.0 technologies. *International Journal of Intelligent Networks, 3,* 150–164. https://doi.org/10.1016/j.ijin.2022.09.004

Kakraliya, S. K., Jat, H. S., Singh, I., Gora, M. K., Kakraliya, M., Bijarniya, D., Sharma, P. C., & Jat, M. L. (2022). Energy and economic efficiency of climate-smart agriculture practices in a rice–wheat cropping system of India. *Scientific Reports, 12*, 8731. https://doi.org/10.1038/s41598-022-12686-4

Komarek, A., Thurlow, J., De Pinto, A., Kwon, H., & Koo, J. (2019). Economywide effects of climate-smart agriculture in Ethiopia. *Agricultural Economics, 50*(6), 765–778. https://doi.org/10.1111/agec.12523

Kpenekuu, F., Antwi-Agyei, P., Nimoh, F., Dougill, A., Banunle, A., Atta-Aidoo, J., Baffour-Ata, F., Agyekum, T. P., Addai, G., & Guodaar, L. (2025). Cost and benefit analysis of climate-smart agriculture interventions in the dryland farming systems of northern Ghana. *Regional Sustainability, 6*(1), 100196. https://doi.org/10.1016/j.regsus.2025.100196

Kuehne, G., Llewellyn, R., Pannell, D. J., Wilkinson, R., Dolling, P., Ouzman, J., & Ewing, M. (2017). Predicting farmer uptake of new agricultural practices: A tool for research, extension and policy. *Agricultural Systems, 156*, 115–125. https://doi.org/10.1016/j.agsy.2017.06.007

Lowder, S. K., Skoet, J., & Raney, T. (2016). The number, size, and distribution of farms, smallholder farms, and family farms worldwide. *World Development, 87*, 16–29. https://doi.org/10.1016/j.worlddev.2015.10.041

McCarthy, N., Lipper, L., & Zilberman, D. (2017). Economics of Climate Smart Agriculture: An Overview. In *Natural resource management and policy* (pp. 31–47). https://doi.org/10.1007/978-3-319-61194-5_3

Mizik, T. (2021). Climate-smart agriculture on small-scale farms: A systematic literature review. *Agronomy, 11*(6), 1096. https://doi.org/10.3390/agronomy11061096

Mohamed, E. S., Belal, A., Abd-Elmabod, S. K., El-Shirbeny, M. A., Gad, A., & Zahran, M. B. (2021). Smart farming for improving agricultural management. *The Egyptian Journal of Remote Sensing and Space Science, 24*(3), 971–981. https://doi.org/10.1016/j.ejrs.2021.08.007

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & The PRISMA Group. (2010). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *International Journal of Surgery, 8*(5), 336–341. https://doi.org/10.1016/j.ijsu.2010.02.007

Mujeyi, A., & Mudhara, M. (2020). Economic analysis of climate-smart agriculture technologies in maize production in smallholder farming systems. In W. Leal Filho, N. Oguge, D. Y. Ayal, L. Adeleke, & I. da Silva (Eds.), *African handbook of climate change adaptation* (pp. 1–16). Springer. https://doi.org/10.1007/978-3-030-42091-8_17-1

Navarro, E., Costa, N., & Pereira, A. (2020). A systematic review of IoT solutions for smart farming. *Sensors, 20*(15), 4231. https://doi.org/10.3390/s20154231

Navarro-Hellín, H., Martínez-Del-Rincon, J., Domingo-Miguel, R., Soto-Valles, F., & Torres-Sánchez, R. (2016). A decision support system for managing irrigation in agriculture. *Computers and Electronics in Agriculture, 124*, 121–131. https://doi.org/10.1016/j.compag.2016.04.003

Nowak, B. (2021). Precision agriculture: Where do we stand? A review of the adoption of precision agriculture technologies on field crops farms in developed countries. *Agricultural Research, 10*(4), 515–522. https://doi.org/10.1007/s40003-021-00539-x

Papadopoulos, G., Arduini, S., Uyar, H., Psiroukis, V., Kasimati, A., & Fountas, S. (2024). Economic and environmental benefits of digital agricultural technologies in crop production: A review. *Smart Agricultural Technology, 8*, 100441. https://doi.org/10.1016/j.atech.2024.100441

Pope, M., & Sonka, S. (2020). Quantifying the economic benefits of on-farm digital technologies. *Farmdoc daily, 10*(40). Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

Poudel, S., Thapa, R., & Mishra, B. (2024). A farmer-centric cost–benefit analysis of climate-smart agriculture in the Gandaki River Basin of Nepal. *Climate, 12*(9), 145. https://doi.org/10.3390/cli12090145

Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0:

Broadening Responsible innovation in an era of smart Farming. *Frontiers in Sustainable Food Systems, 2*. https://doi.org/10.3389/fsufs.2018.00087

Sain, G., Loboguerrero, A. M., Corner-Dolloff, C., Lizarazo, M., Nowak, A., Martínez-Barón, D., & Andrieu, N. (2017). Costs and benefits of climate-smart agriculture: The case of the Dry Corridor in Guatemala. *Agricultural Systems, 151*, 163–173. https://doi.org/10.1016/j.agsy.2016.05.004

Su, Y., & Wang, X. (2021). Innovation of agricultural economic management in the process of constructing smart agriculture by big data. *Sustainable Computing: Informatics and Systems, 31*, 100579. https://doi.org/10.1016/j.suscom.2021.100579

Van der Burg, S., Wiseman, L., & Krkeljas, J. (2021). Trust in farm data sharing: Reflections on the EU code of conduct for agricultural data sharing. *Ethics and Information Technology, 23*, 185–198. https://doi.org/10.1007/s10676-020-09543-1

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming: A review. *Agricultural Systems, 153*, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023

World Bank. (2021). *Digital agriculture profiles.* World Bank.

Yoon, C., Lim, D., & Park, C. (2020). Factors affecting adoption of smart farms: The case of Korea. *Computers in Human Behavior, 108*, 106309. https://doi.org/10.1016/j.chb.2020.106309